Specifying the Forecast Generating Process for Exchange Rate Survey Forecasts

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Abstract This paper contributes to the literature on the modeling of survey forecasts using learning variables. We use individual industry data on yen-dollar exchange rate predictions at the two week, three month, and six month horizons supplied by the Japan Center for International Finance. Compared to earlier studies, our focus is not on testing a single type of learning model, whether univariate or mixed, but on searching over many types of learning models to determine if any are congruent. In addition to including the standard expectational variables (adaptive, extrapolative, and regressive), we also include a set of interactive variables which allow for lagged dependence of one industry's forecast on the others. Our search produces a remarkably small number of congruent specifications-even when we allow for 1) a flexible lag specification, 2) endogenous break points and 3) an expansion of the initial list of regressors to include lagged dependent variables and use a General-to-Specific modeling strategy. We conclude that, regardless of forecasters' ability to produce rational forecasts, they are not only "different," but different in ways that cannot be adequately represented by learning models.

Keywords: Learning Models, Exchange Rate, Survey Forecasts.

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1 Introduction and Background

To what extent are differences in the performance of exchange rate forecasters reflected in differences in expectational models? For example, suppose we evaluate performance based on rationality criteria. If more than one forecaster produces rational forecasts at a given horizon, does that imply that their forecast generating processes (FGPs) are identical (or similar) and also identical (or similar) to the data generating process (DGP) of the realization? Conversely, is the rejection of rationality for at least one forecaster at a given horizon reflected in a lack of homogeneity in the individual FGPs?

Another motivation for studying the exchange rate FGP is the poor forecasting performance of the exchange rate equation in large-scale macroeconomic models. The exchange rate is typically modeled by an uncovered interest rate parity condition, with the maintained assumption that the current exchange rate is the rational expectation of the future exchange rate (see Bryant (1995)).[1] In his evaluation of the performance of various structural models in predicting the direction of exchange rate change, Pilbeam (1995, p. 1013) noted: "What is far more crucial than the economic model is the expectations mechanism that is applied to a model. An extrapolative or adaptive expectations mechanism leads to a markedly superior performance than static, regressive, and rational expectations mechanisms."

The Japan Center for International Finance (JCIF) biweekly survey of the yen-dollar exchange rate predictions of Japanese forecasters is one of the few surveys of exchange rate forecasters that is available in disaggregated form. Using the JCIF industry-level forecasts, we conduct a model specification search to study industry-level forecast generating processes.[2]

Cohen et al. (2006) find that, for each industry group in the JCIF survey, the ability to produce unbiased forecasts deteriorates with horizon.[3] Exporters consistently perform worse

[1]A terminal condition normally sets the end of horizon exchange rate to a long-run equilibrium.

[2]See Appendix 1 for a description of the data. Ito (1990, 1994), Bryant (1995) and Elliott and Ito (1999) contain detailed descriptions of this database.

[3]Cohen et al. (2006) are unable to reject unbiasedness for any group at the one-month horizon, but reject unbiasedness for all groups at the six-month horizon, because the forecast errors at the latter horizon are

than the other industry groups, with a tendency toward depreciation bias. Using only two years of data, Ito (1990) found the same result for exporters, which he described as a type of "wishful thinking".

Cohen et al. (2006) also find a general failure of weak efficiency, both with respect to specific information set variables (single and cumulative lags of the mean forecast error, mean forecasted depreciation, and actual depreciation) and in LM tests for general serial correlation of order h (the forecast horizon) or greater. And in both unbiasedness and efficiency tests, they reject micro-homogeneity of industry-group parameters for virtually all regressions.[4] In this paper, we investigate the possibility that the widespread failure of micro-homogeneity in rationality tests is reflected in diversity of the FGPs.

The extant literature that studies learning processes using survey forecasts has focused almost exclusively on static specifications of the three basic models—adaptive, extrapolative, and regressive, and in some cases a mixed model that combines two or more of the basic processes. This paper extends that literature in several ways. First, we add a fourth type of learning process. Recognizing the growing literature on the role of strategic interaction in the individual forecast generating process,[5] we include a set of variables for the difference between one forecaster's prediction and the most recently available (lagged) forecast of others (either individually or grouped into a mean).[6]

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nonstationary. They conduct these tests by regressing the forecast error on a constant using a Newey-West-Bartlett correction for residual serial correlation. Some authors maintain that the tendency of cointegration tests to over-reject the null of cointegration renders any rejection questionable. In this interpretation, we simply cannot conduct consistent tests for unbiasedness at the six-month level.

[4]Their rejection of micro-homogeneity, irrespective of the ability of industry-groups to form unbiased forecasts, is somewhat counterintuitive. Micro-homogeneity should be more likely if there are no rejections of unbiasedness. Evidently, there is a sufficient variation in the estimated bias coefficient across groups and/or high precision of these estimates to make the micro-homogeneity test quite sensitive.

[5]This literature, in turn, is a subset of the literature on asymmetric loss functions. In this case, the optimal forecast may not be the minimum means squared error forecast. For example, it may pay for some forecasters with sufficient reputational capital to produce extreme forecasts, if the forecaster's brand-name recognition is enhanced more than his record for forecast accuracy is damaged. Laster et al. (1999) called this practice "rational bias." Ehrbeck and Waldmann (1996) tested hypotheses in which a less able forecaster moderates his personal forecast by weighting it with the prediction pattern of more able forecasters (see also Batchelor and Dua, 1990a,b). In addition to the literature on strategic interactions cited in the context of asymmetric loss functions, see also Flieth and Foster (2002).

[6]Ito (1990) used this type of specification as a *dependent* variable in his measure of forecaster heterogeneity.

Second, whether in simple or mixed models, we allow for the fact that the best fit for each learning process may come from a number of past lags, not simply the most recent.[7]

Third, in our simple and mixed models of learning processes, we allow for endogenous structural change in each coefficient.[8] As noted by Griliches and Mairesse (1990) in their seminal study of panel data on firms' production functions, "[i]nstability may be the main problem with our data, rather than heterogeneity." In the exchange rate literature, Goldberg and Frydman (1996) reject the rational expectations assumption in favor of a "qualitative rationality" in which inherently imperfect knowledge can be used only to predict the direction of the exchange rate movement. In their model, adjustment to the permanent component of shocks is reflected in structural shifts in expectations functions.[9] In this vein, Gygax and Sawyer (2003) claim that "[d]ependence which is stationary does not lead to learning." We use the Bai-Perron (BP) method (1998; 2003) to identify, estimate, and test for such parametric shifts.

Even if the structural breaks do not correspond to identifiable changes in exchange rate regimes, they may reflect forecaster learning behavior. Linear combinations of conventional learning models have been used by Frankel and Froot (1987) and subsequent researchers. One vein of research (Frankel and Froot, 1986, 1990) attempts to fit actual exchange rates to a time-varying weighted average of a chartists/noise trader variable (for which forecasts follow a bandwagon or random walk and therefore tend to be destabilizing) and a fundamentals variable (for which forecasts satisfy the rational expectations hypothesis and tend to be stabilizing). The weights are updated each period, shifting in favor of the model that has been the most accurate recently. The second vein of modeling, which we pursue here, attempts to fit expectations themselves to the more general set of learning processes.

[7]Some authors allow for more than one lag of the regressor, but they do not allow a flexible lag specification with more than just a few lags. Few authors report the results of specification searches with more than a few lags in their general model. Prat and Uctum (2000) are an exception, but only for the extrapolative model.

[8]This is an alternative to comparing the estimated coefficients over arbitrary subsamples of the data, as in, e.g., Ito (1994).

[9]Their structural variables are based on the monetary model, not solely on *ad hoc* learning variables models such as the ones we use.

This "mixed model" approach subsumes the chartist-fundamentalist approach as particular coefficient restrictions. Most researchers have confined themselves to estimating a linear combination of the conventional static extrapolative, adaptive, and regressive specifications without structural change dummies, using survey forecasts that are aggregated over individuals. As mentioned above, modeling individual learning processes may reveal specific differences across forecasters that explain the failure of micro-homogeneity tests for rational expectations.[10]

Fourth, for all but the most general specification, we use a two-stage model selection methodology to choose the variable(s) which provides the best forecasting performance among the four types of learning models at each stage of analysis. Finally, in the third stage, we allow the model to be explicitly dynamic by adding lagged dependent variables to the learning model variables and conducting a general-to-specific model selection process in the spirit of the LSE school.

For each forecaster and horizon, our goal is to search both locally (for each of four types of learning models, over three types of regressor specifications—single variable unlagged, single variable with structural change dummies, and single variable with optimal lag specification) and globally (over all possible variables in all learning models) for congruent models of expectations.[11]

To see the difference between our method and other model selection strategies, consider the approach used by Frankel and Froot (1987) in their seminal paper. After estimating

[10]However, even using disaggregated data, mixed FGPs have not been able to separately identify response coefficients and weights for each learning model. Furthermore, as described by Abou and Prat (2000, p. 291): "In fact, the weighting coefficients...which are implicitly embedded in the parameters of the three processes can *a priori* have two non-exclusive meanings:

- 'the representative agent' [they used aggregate forecast data] formulates his expectation by combining the three basic processes according to subjective proportions (that is, the agent chooses the ERAMLI [a particular specification of mixed model] at any time);
- [a single simple learning model is used at each point in time, and] the weight of each basic process in the ERAMLI depends on its frequency over the estimation period."

Prat and Uctum (2000, p. 265) also discuss this limitation of their mixed process.

[11]A congruent model is one which passes certain tests for white noise residuals. (For a list of such tests see the notes at the end of tables 2.1 - 2.6.)

simple conventional extrapolative, adaptive, and regressive models, these authors then combined these individual learning models into a mixed model. Frankel and Froot (1987) did not report specific results of this exercise. Their rationale (p. 145) provides an interesting counterpoint to our own strategy:

> Clearly, if a high R^2 were our goal, more complicated models could have been reported. We estimated a more general specification for expectations, expanding the information set to include simultaneously the current and lagged spot rates, the long-run equilibrium rate and the lagged expected spot rate ... The R^2s of these more complex permutations were higher than those [for the simple models.] However, the best fits were for models which are unfamiliar compared with the popular formulations above ... The central point of our analysis is to investigate the robustness of a rejection of static expectations, not to settle on any single model of expectations. The goodness of fit statistics ..., however, give us an opportunity to compare the fits of these simple alternative specifications.

Our goal of congruency is clearly more challenging than either confirming the rejection of static expectations against one or more single variable alternatives or maximizing a single measure of model fit.

2 Specifying the Forecast Generating Processes

Since there is evidence that the spot rate and all forecasts are integrated of order one (see Cohen et al. (2006)), to achieve stationarity we follow the convention of expressing the dependent variable in return form, i.e., $(s^e_{i,t,h} - s_t)$, where s is the natural log of the exchange rate at time t, expressed as yen per dollar, and the superscript "e" represents forecaster i's expectation of the spot rate h (biweekly) periods in the future.[12] For each of the four industry groups ($i = 1, 2, 3, 4$), there are two candidate variables for adaptive expectations regressors, one based on last period's expectation $(s_t - s^e_{i,t-1,h})$, the other based on the expectation h periods ago $(s_t - s^e_{i,t-h,h})$. Similarly, there are two extrapolative variables ($s_t - s_{t-1}$ and $s_t - s_{t-h}$). There are also two regressive expectations variables, which measure the deviation of the current spot rate from a proxy for the long-run equilibrium. The first is based on

[12] Hth differences of natural logarithms of forecasts are stationary at the 1% level for all groups. See Cohen et al. (2006).

defining the long-run equilibrium as the six-month forecast of the exchange rate ($s^e_{i,t,12} - s_t$). (This forecast horizon is chosen because it is the longest in the dataset.) The second is based on defining the long-run equilibrium as a moving average of the exchange rates over the past six months ($\overline{s_t} - s_t$), where $\overline{s_t} = \frac{1}{12}\sum_{l=0}^{11} s_{t-l}$. Finally, there are four interactive expectations regressors for each of the four forecaster industry groups. A typical regressor takes the form $s^e_{i,t,h} - s^e_{j,t-1,h}$ for $i = 1, 2, 3, 4$, and $j(\neq i) = 1, 2, 3, 4, m$, where m is the mean forecast of the four groups.[13]

Table 1 describes the three stages of the specification process. The first two rows (stages I and II) refer to sequential stages of analysis; the columns (A, B, and C) refer to type of regression specification. In stage I, we begin by using Hocking's S_p information criterion to choose a (single) unlagged optimal regressor for each of the four learning models.[14]

Then, in IB, we use the same regressor for each learning model that we chose in IA, but allow for structural change using the technique of Bai and Perron (1998; 2003).[15] In IC, we estimate the optimal lag specification (typically not consecutive) for the regressor selected in IA.[16]

[13] The reason for lagging industry j's forecast one (two week) period is that, on the day after the forecast, the JCIF announces the overall mean forecast and each industry's average forecast.

[14] $S_p = \frac{RSS}{(T-k)(T-k-1)}$, where, in the given model, RSS is the residual sum of squares, T is the number of observations, and k is the number of regressors. See Maddala (1992) for discussion of this and other information criteria. Unlike R^2, $\overline{R^2}$ and other model selection statistics, S_p does not assume that any resulting model, including the one which minimizes the criterion, is the true FGP. Nor do we have to know which regressors are in the true FGP. We only need to estimate the variance of the disturbance term in each model. Thus, for comparison purposes, we can legitimately identify the best of a set of possibly misspecified models within each regressor category. We restrict our specification search to the current and lagged values of each learning variable. In stage III we expand our list of candidate regressors to include all learning variables and lagged dependent variables in what Hendry has called a General Unrestricted Model.

[15] We set the BP algorithm to allow up to five structural changes in each parameter. Given this constraint, we follow BP's recommendation for selecting the number of breaks (Bai and Perron, 2003, pp. 15-16) by first testing the null hypothesis of zero breaks against the alternative of more than one break. If the null is rejected, we then use a sequential method to test for each incremental break, based upon a 5% significance level. We allow for different distributions for the data and errors across regimes, although errors are assumed to be asymptotically independent across regimes. To ensure reliable inference, each regime must contain at least 15% of the sample observations. (Thus, each regime contains a minimum of about 30 forecasts, i.e., a 15-month period.) Estimators are consistent in the presence of heteroscedasticity and autocorrelation.

[16] Note that the simple model in column A is nested in column B; we include column A results for comparison with the mainstream literature.

Table 1 Outline of Specification Tests for Learning Models

Stage I: Variable selection		
Based on Hocking's S_p, select one regressor for each of 4 learning model categories (adaptive, extrapolative, regressive, and interactive; see Appendix 1 for variable definitions); then estimate using OLS		
A. Simple (a.k.a "conventional" or single regressor) models	B. "Conventional" specification (single, unlagged variable) with structural change dummies	C. Optimal lag specification (single variable with possible nonconsecutive lags)
Stage II: Mixed learning models		
Using the 4 regressors estimated in IA	Using the 4 regressors estimated in IA, with new set of structural change dummies	Using lags of the 4 regressors estimated in IC
Stage III: General-to-Specific Model Selection		

In stage II, for each of the three specifications (columns A, B, and C), we estimate a mixed model comprised of the optimal variables from each of the four types of learning models.[17] For example, in the case of the conventional specification of column A, the mixed model consists of the optimal extrapolative, adaptive, regressive, and interactive variables as chosen in stage I. In IIB the structural breaks are re-estimated for the four-variable mixed model, using the same regressors as in IIA. These structural breaks are not the union of the sets of structural breaks for each of the four single variable learning models estimated in IB. Attempting to use the latter would result in overlapping regimes. Similarly, in stage IIC, rather than simply defining the "best" set of lagged regressors as the one with the minimum S_p, we use the above-mentioned algorithm due to Hendry and Krolzig (2001) for selecting the model of the forecast generating process.[18]

In stage III we conduct an unrestricted general-to-specific search over the current and lagged values of each of the two extrapolative variables, two adaptive variables, two regressive variables, one interactive variable (the group forecast less the lagged mean forecast),[19] and the lagged dependent variable. It is important to note that, in the first two stages, should we find a congruent specification for a given group and horizon, that specification may not encompass a congruent specification based on the expanded set of candidate regressors in stage III. Thus, in the earlier stages, we use the Hendry and Krolzig (2001) model selection algorithm but not the Hendry and Krolzig (2001) methodology, which begins with a general unrestricted model.

[17]Thus, each of the three categories of mixed models (in columns A, B, and C) nest their single regressor counterparts chosen in stage I.

[18]The possibility of multicollinearity implies that even a path-independent model selection procedure such as that used in Hendry and Krolzig (2001) may not include certain economically relevant regressors in the mixed models. This is another justification for estimating single learning processes in stage I. If a learning process is not significant in either the single learning model of stage I or the mixed model of stage II, then it was correctly omitted from both models. However, if a learning process is significant in stage I but not in stage II, there are two possible reasons: mistaken inclusion in stage I due to omitted variable bias in the single learning model or mistaken exclusion in stage II, due to multicollinearity in the mixed model's regressors. The selection method in Hendry and Krolzig (2001) minimizes both types of errors by testing for the significance of all possible combinations of regressors jointly.

[19]Unlike the models in the earlier stages, conservation of degrees of freedom dictated that we not include interactive expectations variables for all permutations of paired groups.

A congruent model is one which passes certain tests for white noise residuals. (For a list of such tests see the notes at the end of tables 2.1 - 2.6.)[20] In contrast, based on low Durbin-Watson statistics for certain learning models and currencies, Frankel and Froot (1987) use an estimator that includes an AR(1) transformation to whiten the residuals. Of course, this changes the structure of the learning model. (However, other authors testing conventional learning models, either simple or mixed, use OLS estimation and do not test for or allow for departures from i.i.d. Examples include Maddala (1992) and Cavaglia et al. (1993a,b).)[21]

3 Discussion of Learning Models Results

Tables 2.1 - 2.6 summarize the results of specifications tests on the models in our four stage procedure. Below we provide an economic interpretation of the estimated parameters (not reported in the tables). Tables 3.1-3.4 present estimation results for models which pass all tests for congruency. The variable names used in the tables are defined in Appendix 1.

3.1 Conventional Univariate Learning Models

For the one-month horizon, the adaptive coefficients for groups 1 and 2 are positive fractions, indicating elastic, or destabilizing, expectations. For groups 3 and 4 the coefficients are negative fractions and statistically significant, indicating inelastic, or stabilizing, expectations. (Three out of four coefficients are significant at the 5% level.) For all groups but 3, the regressive coefficient is a negative fraction, indicating destabilizing expectations.[22] For all groups but 3, the extrapolative coefficient is a positive fraction, indicating destabilizing

[20]To save space and also because of specification problems discussed in section 3.5 below, we omit individual regression results from noncongruent specifications. These results are available from the authors.

[21]It is also possible to allow for a nonrandom residual structure in the FGP for the wrong reason. See Benassy-Quere et al. (2003). For instance, even though all JCIF *forecasts* are multiperiod (since forecasts are made every two weeks for one, three, and six months), if one uses versions of the *learning models* in which the most recently available data are used (e.g., the most recent one-period change in the realization or the forecast error) for all horizons, there is no lag between the dependent variable (i.e., forecast change) and the information set used to construct the independent variable(s). For example, forecasters do know the $h-k$ period forecast at the time they make the h-period forecast. Thus, the data do not overlap in the Hansen and Hodrick (1980) sense (and so should not have an $MA(h-k)$ structure). Therefore, the residuals in an FGP should be uncorrelated if the FGP is a congruent specification.

[22]These regressive variables are measured as the deviation of time t spot rate from the six-month moving average, whereas the group 3 regressive variable is measured as the deviation of the time t spot rate from the six-month forecast.

expectations. Finally, all groups showed positive interaction with group 3's previous forecast. (Group 3 showed positive interaction with group 2's previous forecast.) In short, there is some evidence for destabilizing expectations at the one-month forecast horizon.

For the three-month horizon, all adaptive coefficients are negative and statistically significant, indicating stabilizing expectations. Similarly, all regressive coefficients are positive and statistically significant, also indicating stabilizing expectations. Three of four extrapolative coefficients are significantly negative, implying stabilizing expectations. Also, it appears that groups 1 and 2 have positive interaction with group 4, while groups 3 and 4 have positive interaction with group 2. In general, then, at the three-month horizon, the regressions show increasing evidence of stabilizing expectations.

For the six-month horizon, the adaptive coefficients also indicate stabilizing expectations, and are greater in absolute magnitude and statistical significance than the three-month horizon. Similarly, the regressive and extrapolative coefficients are all stabilizing and statistically significant. Also, a clear pattern of interaction emerges, in which group 1's forecasts positively and significantly influence the forecasts of nearly all other groups. However, no group's forecasts significantly influence group 2's. Thus, compared with the three-month horizon, stabilizing influences are even more dominant.

Next, we investigate whether these patterns hold when we incorporate all the learning models in a single mixed model of expectation formation.

3.2 Conventional Mixed Learning Models

At the one-month horizon, all adaptive coefficients are stabilizing and significant. They are about the same magnitude as the simple learning models at the three-month horizon. Only two of the extrapolative coefficients are significant, and these are in the destabilizing direction. All four regressive coefficients are destabilizing, and three are statistically significant. Finally, there is a significant positive interaction between group 3 and all other groups. Group 3's forecasts are most closely associated with group 2's.

At the three-month horizon, all adaptive and regressive coefficients are stabilizing, significant, and higher than their one-month counterparts. However, all extrapolative coefficients are now destabilizing at or close to significant levels. There appears to be interaction between group 2 and two other groups as well as between group 3 and two other groups.

At the six-month horizon, while adaptive expectations appear stabilizing as usual, neither regressive nor extrapolative expectations show a clear pattern. Three of four groups show positive interaction with group 1.

In summary, allowing for mixed models of learning weakens the pattern of increasing stability of expectations with increasing horizon that we found with the corresponding simple learning models. Our results contrast somewhat with those of Ito (1994), who, using aggregate data, found stronger evidence of destabilizing expectations at the one-month horizon and stabilizing expectations at the six-month horizon.[23]

3.3 Learning Models with Structural Breaks

At the one-month horizon, all groups showed statistically significant stabilizing adaptive coefficients. However, the significant extrapolative coefficients were mostly destabilizing for groups 1 and 2 and stabilizing for groups 3 and 4. For all groups, the regressive coefficients were uniformly destabilizing. Groups 3 and 4 exhibited mostly stabilizing adaptive coefficients, while the results for groups 1 and 2 were mixed.

At the three-month horizon, only group 4 showed consistently stabilizing adaptive coefficients. The others were mixed. Extrapolative effects were also destabilizing; only group 3 showed consistently stabilizing effects. Again, results for the other groups were mixed and/or insignificant. However, regressive coefficients were nearly all stabilizing across groups.

[23]However, he used different definitions of the long-run equilibrium. One of his measures was a loglinear trend fit to the entire sample period. As Ito notes, this not only requires knowledge that is not in the forecaster's real time information set, but it would also not be valid if the exchange rate has a unit root. Using a longer sample period, we found that there is indeed a unit root (see Cohen et al. (2006)). Ito also used a log linear trend of the exchange rate between two years of current account balance as a measure of the long-run equilibrium. Since the two years (1973 and 1974) occurred prior to the beginning of the survey, it was possible for this measure of long run equilibrium to be in forecasters' information sets, although again, with a longer data set, the assumption of stationarity is questionable.

At the six-month horizon, adaptive coefficients were uniformly stabilizing. Extrapolative coefficients were nearly all insignificant, except for group 1, where they were significant but mixed. Few regressive coefficients were significant; those that were tended to be stabilizing.

In fact, all models, mixed as well as simple, exhibit at least one structural break. Many coefficients change sign across structural breaks, illustrating the extreme instability of the learning models. Ito (1994) divided his eight year sample (1985-1993) into four two-year subperiods and also found evidence of parameter instability. In short, allowing for structural breaks does not seem to produce a clearer pattern of short-run destabilizing and long-run stabilizing behavior of expectations. The interesting result from using the Bai-Perron method to allow the data to "select" the break points is that there is a much greater similarity of break points within groups (across learning variables and horizons) than across groups (for given learning variables and horizons). Thus, differences in temporal instability of coefficients of learning models may be one manifestation of the heterogeneity of the FGPs.

However, even allowing for structural breaks, we rarely find congruent models. (Congruent models are indicated by a **C** in tables 2.1 - 2.6.) Hence, an alternative interpretation is that structural breaks represent evidence of model misspecification. Overall, when considering all of our "local" (i.e., stages I and II) specifications–(48) simple learning models with and (48) without structural breaks (tables 2.1 - 2.2), (48) simple learning models with optimal lag specifications (table 2.3), (12) conventional mixed learning models with and (12) without structural breaks (table 2.4), and (12) optimal lag mixed models (table 2.5)–we find only four congruent models out of 180. The output for the four congruent models is shown in tables 3.1- 3.4. Only one is for a simple learning model with no lags or structural change (group 3 at a six-month horizon using an adaptive model).[24] Three are for the mixed model with (from one to three) structural breaks (group 1 at the six-month horizon and group 4 at the one- and six-month horizons).[25] Although group 1's regressive coefficient tended to

[24]The negative coefficient is consistent with stabilizing expectations.

[25]Because no more than one model is congruent for a given group and horizon, no encompassing tests are possible.

be stabilizing, even at the one-month horizon, the overall results for the congruent mixed models are at least broadly consistent with the chartist-fundamentalist dichotomy of short-run destabilizing and longer-run stabilizing tendencies. However, these tendencies appear to reside within a single industry group.

3.4 An Alternative: Implementing Automatic Model Selection via a General-to-Specific Modeling Strategy

It is more in the spirit of the general-to-specific methodology for selecting a congruent model to begin "testimation" (c.f. Trivedi 1984) by including lagged dependent variables in the general unrestricted model (GUM). This allows for learning to be truly dynamic, even if coefficient interpretation does not fit the conventional learning model framework. The Gets modeling strategy seems especially well-suited to fitting learning models to forecasts. In this setting, theory does not impose strong restrictions on the parameters, thereby permitting emphasis to be placed on explaining a great deal of time-series variation, with little cost of sacrificing identifying relationships.[26,27] Thus, our GUM consists of the current value and twelve lags each of the two extrapolative variables, two adaptive variables, two regressive variables, one interactive variable (the group forecast less the lagged mean forecast), and the lagged dependent variable–a total of 103 variables in all. Given sample sizes of slightly over 200 biweekly forecasts, initial tests on the GUM generally have about 100 degrees of freedom. Therefore, we use F tests, since these exhibit better small sample properties than the χ^2. (See Hendry and Krolzig (2001)).

Tables 3.3 - 3.4 report the estimation of each of the congruent models discovered in the general-to-specific search conducted in stage III. Of the twelve models we fit (four groups times three horizons), we find congruent models (at the 5% level for all the specification tests) for five groups–groups 2 and 3 at the one month horizon, and groups 1, 3 and 4 at the three month horizon. (These models have between six and 15 regressors.) These

[26] See Faust and Whiteman (1997).

[27] Because our GUM contains so many variables relative to any reasonable learning process, we selected the "conservative" modeling strategy, which minimizes the non-deletion probabilities of irrelevant variables.

results represent a vast improvement over the congruency results from the first two stages. Yet, for the majority of survey forecasts, learning models–even when augmented with lagged dependent variables–do not pass a battery of standard diagnostic tests.

Next, we examine the stability properties of the coefficients in the general-to-specific (GTS) estimations. (In models in which there were two of a given type of regressor, e.g., current value and third lag of the extrapolative regressor E1, we determined stability using the sum of the coefficients.) For the two congruent models at the one month horizon, the coefficients of the adaptive variable are destabilizing in group 2 and stabilizing in group 3. Similarly, the coefficients of the extrapolative variable are stabilizing in group 2 and destabilizing in group 3. As theory would suggest, at the one month horizon, neither regressive variable is significant in any of the four final models. For the three congruent models at the three month horizon, all adaptive variables have net stabilizing coefficients; however, extrapolative and regressive variables have both stabilizing and destabilizing coefficients.

The lagged forecast appears in nine of the twelve final models, and in three of the five congruent models. This suggests that, overall, the models exhibit a dynamic component that is not captured by the learning variables.

Finally, the deviation of a given group's forecast from the lagged mean appears in all twelve final models. These interactive variables, including lags, account for between one fifth and one half the regressors in the GTS congruent models. Thus, regardless of horizon, a given group's forecast exhibits a systematic reliance on the (past) forecasts of others–either individually or as reflected in the mean.

3.5 Conclusion: Model specification problems

In the present context of modeling foreign exchange rate expectations, an important question is "how well can learning and innovation themselves be modeled by constant parameter processes?" (Doornik and Hendry, 1994, p. 295) When an FGP involves learning, modeling strategy would seem to imply some sort of time-variation in parameters, i.e., nonstationarity, even in series that are I(0). The Bai-Perron technique shows no pattern of breaks across forecasters that corresponds to changes in foreign exchange regimes, such as those that occurred at Plaza meeting in September 1985 (which let the dollar depreciate) or the Louvre meeting (which agreed to stabilize the exchange rate within a target zone). Hence, such variation in a given set of regression coefficients is considered suboptimal from an encompassing perspective. However, Doornik and Hendry (1994) recognize that there is a type of nonstationarity that cannot be removed by differencing, a cointegrated transformation, or parameter shifts. This is “inherent non-stationarity owing to innovative human behaviour or natural processes, which as yet we do not know how to remove or model” (1994, p. 295). Using a mechanical model selection technique, even with lags of regressors from standard learning models, runs the risk of settling on “complicated mechanisms dependent on mixtures of unlikely but time-independent events, which would seem to be non-stationary despite having constant unconditional moments.” (1994, p. 295)

In the introduction we noted that Cohen et al. (2006) found that micro-homogeneity tests for equal parameters across groups failed at very low significance levels in both unbiasedness and efficiency tests. Not only are forecasters “different”, they are different in ways that cannot be adequately represented by learning models–in most cases, even when augmented with lagged dependent variables. Modeling forecast generating processes would seem to be at least as challenging a task as modeling data generating processes.

Table 2.1 Results of Congruency Tests:

Stage I: Simple Learning Models (one category of learning variable)

IA: "Conventional" specification (single unlagged variable)

Horizon/Specification	Group 1	Group 2	Group 3	Group 4
1 mo./Adaptive	A2G1 (1,2)	A2G2 (1,2,3)	A1G3 (1)	A1G4 (1,2,3)
Regressive	R2 (1,2)	R2 (1,3)	R1G3 (1,2)	R2 (1,2,4,5,6)
Interactive	IG13 (1,2)	IG23 (1,2)	IG32 (1,2)	IG43 (1,2,3)
Extrapolative	E2 (1,2)	E2 (1,2,3)	E1 (1,2)	E2 (1,2,3)
3 mo./Adaptive	A1G1 (1,2)	A1G2 (1,2)	A1G3 (1)	A1G4 (1,2,3,6)
Regressive	R1G1 (1,2)	R1G2 (1,2,4,5)	R1G3 (1,2)	R1G4 (1,2,3,4,5)
Interactive	IG15 (1,2,3)	IG24 (1,2,3)	IG32 (1,2)	IG43 (1,2,3,4,5)
Extrapolative	E2 (1,2)	E1 (1,2,3)	E1 (1,2,3)	E1 (1,2,3)
6 mo./Adaptive	A1G1 (1,2,3)	A1G2 (3,6)	A1G3 **(C)**	A1G4 (1,3,6)
Regressive	R2 (1,2,3,4,5)	R2 (1,2,4,5,6)	R2 (1,2,4,5)	R2 (1,2,3)
Interactive	IG13 (1,2,3)	IG21 (1,2,3,6)	IG31 (1,2)	IG41 (1,2,4,5)
Extrapolative	E2 (1,2,3,6)	E2 (1,2,4,5,6)	E2 (1,2,4,5,6)	E1 (1,2,3)

Note: For each horizon and model, right hand side variables are defined in appendix 1. Following the variable name, numbers in parentheses indicate congruency (C) or the specification test(s) which fails at the 5% significance level. Notation for Congruency Tests: C = congruent model; Failure of congruency due to 1 = AR1-2 test; 2 = ARCH 1-2 test; 3 = Normality; 4= Heteroscedasticity; 5= Heteroscedasticity-X; 6 = RESET. Variable I(t) is a dummy variable used to remove the effect of an outlier in period t. Numbers(s) in hard brackets in IB and IIB indicate break points using the Bai-Perron sequential procedure at the 5% significance level.

Table 2.2 Results of Congruency Tests Continued

IB: "Conventional" specification (single unlagged variable) with structural change dummies

Horizon/Specification	Group 1	Group 2	Group 3	Group 4
1 mo./Adaptive	A2G1 (1,2,4,5)	A2G2 (1,2,3)	A1G3 (1,3)	AIG4 (1,2,3,4,5)
	[66,127,169]	[65]	[130]	[72]
Regressive	R2 (1)	R2 (1,3)	R2 (1,3)	R2 (1,4,5)
	[69,126]	[54,107]	[56, 89,130]	[116]
Interactive	IG13 (1,2,3)	IG23 (1,2,3)	IG14 (1,2)	IG43 (1,2,3)
	[69,127,169]	[73]	[130]	[75,116]
Extrapolative	E2 (1,2)	E2 (1,2,3)	E1 (1)	E2 (1,2,3,4,5,6)
	[69,127,169]	[65]	[130]	[130]
3 mo./Adaptive	A1G1 (1,2,4,5)	A2G2 (1)	A1G3 (1)	A1G4 (1,2,4,5,6)
	[32, 82,124]	[32, 78,120]	[107]	[78]
Regressive	R1G1 (1,2,6)	R1G2 (1,2)	R1G3 (1,2,3,4,5)	R1G4 (1,2,3,4,5)
	[68]	[65]	[120]	[72]
Interactive	IG14 (1,2,3)	IG24 (1,2)	IG32 (1,2,4,5)	IG42 (1,2)
	[79,124,168]	[78,120]	[51,86,120]	[78]
Extrapolative	E2 (1,2,4,5)	E2 (1)	E1 (1,2)	E1 (1,2)
	[32,82,124]	[33,78,120]	[51,87,120]	[78]
6 mo./Adaptive	A1G1 (1,2,4,5)	A1G2 (1)	A1G3 (4,5)	A1G4 (1,3)
	[82,140,179]	[78]	[148]	[78,110,142]
Regressive	R2 (1,2)	R2 (1,2,4,5)	R2 (1,2,3,4,5)	R2 (1,2,4,5)
	[68]	[183,151]	[32]	[32,64,176]
Interactive	IG13 (1,2,3,5)	IG21 (1,2,4,5)	IG32 (1,2,6)	IG32 (1,2,3)
	[83,144,181]	[50,84,149]	[50,92,146]	[79,118]
Extrapolative	E2 (1,2,6)	E2 (1,2)	E2 (1,2,4,5)	E2 (1,2,4,5)
	[80,144,181]	[78,166]	[87,148]	[78,151]

Note: For each horizon and model, right hand side variables are defined in appendix 1. Following the variable name, numbers in parentheses indicate congruency (C) or the specification test(s) which fails at the 5% significance level. Notation for Congruency Tests: C = congruent model; Failure of congruency due to 1 = AR1-2 test; 2 = ARCH 1-2 test; 3 = Normality; 4= Heteroscedasticity; 5= Heteroscedasticity-X; 6 = RESET. Variable I(t) is a dummy variable used to remove the effect of an outlier in period t. Numbers(s) in hard brackets in IIB and IIIB indicate break points using the Bai-Perron sequential procedure at the 5% significance level.

Table 2.3 Results of Congruency Tests Continued

IC: Optimal lag specification (single variable with possible multiple nonconsecutive lags)

Horizon/Specification	Group 1	Group 2	Group 3	Group 4
1 mo./Adaptive	A1G1 or A2G1 (1,2)	A2G2 (1)	A1G3 (1)	A1G4 or A2G4 (1,2,3)
	[INT]	[INT,1,3,4;I17,I32,I64]	[INT,0,12;I101]	[INT]
Regressive	R2 (1,2)	R2 (1)	R1G3 (1,2)	R1G4 (1,2)
	[INT,0,6,11]	[INT,0,5,I32,I64,I155]	[INT,0,10]	[INT,0]
Interactive	E1 (1,2,5)	E2 (1)	E1 or E4 (1,2)	E1 or E2 (1,2,3)
	[INT,0,2,4]	[INT,0,2,4;I17,I32,I64]	[INT]	[INT]
Extrapolative	IG13 (1,2)	IG2M (1,4,5)	IG32 (1,2)	IG43 (1,2)
	[INT,0,1,2,3,4,5]	[INT,0,1,2,4;I64]	[INT,2,4,5,9]	[INT,0,1,2,4,5,7;I106]
3 mo./Adaptive	A1G1 (1,2)	A1G2 (1)	A1G3 (1,2)	A1G4 (1,2)
	[INT,0,1,8,10;I92,I110]	[INT,0,2,8;I103]	[0,1,3]	[INT,0,1,6,11]
Regressive	R1G1 (1,2)	R1G2 (1,2,5)	R1G3 (1,2,4,5)	R1G4 (1,2)
	[INT,0,3]	[INT,0,5]	[0]	[INT,0,7]
Interactive	E1 or E2 (1,2)	E1 or E2 (1,2,3)	E1 (1,2,3)	E2 (1,2,3)
	[INT]	[INT]	[0,1,2,10]	[INT;I58]
Extrapolative	IG15 (1,2)	IG21 or IG24	IG31 or IG32	IG42 or IG43
		or IG25 (1,2,3)	or IG35 (1,2,3,4,5,6)	or IG45 (1,2,3)
	[INT,0]	[INT]	[]	[INT]
6 mo./Adaptive	A2G1 (1)	A1G2 (1,4,5)	IG3 (2)	A1G4 (1,6)
	[INT,0,1,3;I102]	[INT,0,1,7;I37,I101]	[0,1,2]	[INT,0,1,3]
Regressive	R2 (1,2,3,4,5)*	R2 (1,2,4,5,6)*	R2 (1,2,4,5,6)*	R2 (1,2,3,4,5)*
	[12]	[INT,0]	[0,1]	[0,5]
Interactive	E2 (1,2,3,6)	E1 (1,2)	E1 (1,2)	E1 (1,2,3)
	[INT,0]	[INT,0,1,3]	[0.1,2,3,4,5,6,7]	[INT,0,1,3,5]
Extrapolative	IG13 (1,2,3)	IG2M (1,2)	IG32 (1,2)	IG42 (1,2,6)
	[11]	[INT,3]	[0]	[0,2;I157]

Note: For each horizon and model, right hand side variables are defined in appendix 1. Following the variable name, numbers in parentheses indicate congruency (C) or the specification test(s) which fails at the 5% significance level. Notation for Congruency Tests: C = congruent model; Failure of congruency due to 1 = AR1-2 test; 2 = ARCH 1-2 test; 3 = Normality; 4= Heteroscedasticity; 5= Heteroscedasticity-X; 6 = RESET. Variable I(t) is a dummy variable used to remove the effect of an outlier in period t. Numbers in hard brackets in IIC and IIIC indicate lag length(s) of optimal specification. An asterisk indicates that we must use lags of R2 as an optimal regressor, since Y6Gi=R1Gi by construction.

Table 2.4 RESULTS OF CONGRUENCY TESTS CONTINUED

Stage II: Mixed Learning Models

IIA: "Conventional" mixed model
using regressors separately fitted in IA

Horizon	Group 1	Group 2	Group 3	Group 4
1 mo.	(1,2)	(1,3)	(1)	(1,5)
3 mo.	(1,2,5)	(1,2,4,5)	(1,4,5)	(1,6)
6 mo.	(1,3,4,5,6)	(1,3)	(1)	(1,3)

IIB: "Conventional" mixed model with structural change dummies
using regressors separately fitted in IA

Horizon	Group 1	Group 2	Group 3	Group 4
1 mo.	(1) [62,123]	(1,3) [64,111]	(1,2,3,6) [123,170]	**(C)** [52,84,130]
3 mo.	(1,2,6) [65,141]	(1,3) [70]	(1,3) [51 85 117]	(1,3) [33,70]
6 mo.	**(C)** [79 119 183]	(3,4,5,6) [81]	(3) [71]	**(C)** [70]

Note: For each horizon and model, right hand side variables are defined in appendix 1. Following the variable name, numbers in parentheses indicate congruency (C) or the specification test(s) which fails at the 5% significance level. Notation for Congruency Tests: C = congruent model; Failure of congruency due to 1 = AR1-2 test; 2 = ARCH 1-2 test; 3 = Normality; 4= Heteroscedasticity; 5= Heteroscedasticity-X; 6 = RESET. Variable I(t) is a dummy variable used to remove the effect of an outlier in period t. Numbers(s) in hard brackets in IB and IIB indicate break points using the Bai-Perron sequential procedure at the 5% significance level.

Table 2.5 Results of Congruency Tests Continued

IIC: Optimal Lag Mixed Model using regressors separately fitted in IC				
Horizon	Group 1	Group 2	Group 3	Group 4
1 mo.	(1,2) [INT,R2(0,6,11), E1(0,2,4),IG13(1,2,3,4,5)]	(1) [INT,A2G2(1,3,4),R2(0,5), E2(0,2,4),IG2M(0,1,2,4); I17,I32, I64, I155]	(1) [INT,A1G3(0,12), R1G3(0,10),IG32(2,4,5,9); I101]	(1,2,3) [INT,R1G4(0), IG43(0,1,2,4,5,7);I106]
3 mo.	(1,5,6) [INT,A1G1(0,1,8,10), R1G1(0,3),IG15(0); I92,I102]	(1,2) [INT,A1G2(0,2,8), R1G2(0,5);I103]	(1,4,5) [A1G3(0,1,3),R1G3(0), E1(0,1,2,10)]	(1,2) [A1G4(0,1,6,11,12), R1G4(0,7),I58]
6 mo.	(1,5) [INT,A2G1(0,1,3),R2(12), E2(0),IG13(11);I102]	(4,5) INT,A1G2(0,1,7),R2, E1(0,1,3),IG2M(3); I37,I101]	(1,2,5) [A1G3(0,1,2),R2(0,1), E1(0,1,2,3,4,5,6,7),IG32(0)]	(1) [INT,A1G4(0,1,2,3), R2(0,5),E1(0,1,3,5), IG42(0,2) ;I57]

Note: For each horizon and model, right hand side variables are defined in appendix 1. Following the variable name, numbers in parentheses indicate congruency (C) or the specification test(s) which fails at the 5% significance level. Notation for Congruency Tests: C = congruent model; Failure of congruency due to 1 = AR1-2 test; 2 = ARCH 1-2 test; 3 = Normality; 4= Heteroscedasticity; 5= Heteroscedasticity-X; 6 = RESET. Variable I(t) is a dummy variable used to remove the effect of an outlier in period t. Numbers in hard brackets in IC and IIC indicate lag length(s) of optimal specification. An asterisk indicates that we must use lags of R2 as an optimal regressor, since Y6Gi=R1Gi by construction.

Table 2.6 Results of Congruency Tests Continued

Stage III: General-to-Specific Models				
Horizon	Group 1	Group 2	Group 3	Group 4
1 mo.	(1) [INT,A1G1(0,1), E2(1),IG1M(0,1)]	**(C)** [Y1G2(1,2,3),A1G2(1), E1(0,3),IG2M(0,1,3)]	**(C)** [A1G3,E1(1,2) IG3M(0,1,2)]	(4,5) [Y1G4(1),E1(0,1), IG4M(0,1)]
3 mo.	**(C)** [Y3G1(1),A1G1(0,1), R1G1,E1(0,1),IG1M(0,1)]	(2,3) [Y3G2(1),A1G2,R1G2, E1(0,1),IG2M(0,1)]	**(C)** [A1G3,R1G3,R2,E1(1), IG3M(0,1,10)]	**(C)** [Y3G4(1,2,3),A1G4(0,1,2), R1G4,R2(1,2,3), E1(0,3),IG4M(0,1,2)]
6 mo.	(4,5) Y6G1(1,2),A1G1(0,3,4,9), E1(1),E2(9),IG2M(0,1,5)]	(5) [Y6G2(1,2),A1G2(0,1), R2(0,1),IG2M(0,1)]	(5) [Y6G3(1),A1G3(0,1), E1(0,1),IG3M(0,1)]	(1) [Y6G4(4),A1G4(0,3),R2(1), E1(1,3),IG4M(0,1)]

Note: For each horizon and model, right hand side variables are defined in appendix 1. Following the variable name, numbers in parentheses indicate congruency (C) or the specification test(s) which fails at the 5% significance level. Notation for Congruency Tests: C = congruent model; Failure of congruency due to 1 = AR1-2 test; 2 = ARCH 1-2 test; 3 = Normality; 4= Heteroscedasticity; 5= Heteroscedasticity-X; 6 = RESET. Variable I(t) is a dummy variable used to remove the effect of an outlier in period t.

Table 3.1 Output for Congruent Models

IA: "Conventional" specification (single unlagged variable)

Horizon/Group	Regressor	Coefficient	SE	t-stat
6 mo./Group 3	A1G3	-0.753	0.024	-30.820
N=209				

IIB: "Conventional" mixed model with structural change dummies

Horizon/Group	Regressor	Coefficient	SE	t-stat
1 mo./Group 4	A1G4-1	-0.338	0.048	-6.994
N =215	A1G4-2	-0.494	0.081	-6.078
No. Var = 20	A1G4-3	-0.473	0.058	-8.127
	A1G4-4	-0.451	0.046	-9.808
	R2-1	-0.048	0.014	-3.378
	R2-2	-0.026	0.026	-1.010
	R2-3	-0.069	0.015	-4.601
	R2-4	0.005	0.008	0.643
	IG43-1	0.512	0.047	10.858
	IG43-2	0.624	0.096	6.527
	IG43-3	0.361	0.054	6.659
	IG43-4	0.494	0.045	10.936
	E2-1	-0.069	0.028	-2.491
	E2-2	-0.109	0.042	-2.589
	E2-3	0.003	0.035	0.097
Break dates	E2-4	-0.048	0.024	-1.995
52	Constant-1	-0.002	0.001	-1.155
84	Constant-2	-0.006	0.001	-4.515
130	Constant-3	-0.003	0.001	-3.665
	Constant-4	0.001	0.001	1.397

Note: number after dash in regressor name represents subset of data determined by structural breaks. The number of subsets of data is one more than the number of structural breaks.

Table 3.2 Output for Congruent Models Continued

IIB: "Conventional" mixed model with structural change dummies (continued)

Horizon/Group	Regressor	Coefficient	SE	t-stat
6 mo./Group 1	A1G1-1	-0.603	0.056	-10.812
N=209	A1G1-2	-0.312	0.074	-4.216
No. Var = 20	A1G1-3	-0.655	0.069	-9.526
	A1G1-4	-0.303	0.108	-2.814
	R2-1	0.041	0.039	1.056
	R2-2	0.130	0.059	2.222
	R2-3	-0.074	0.076	-0.971
	R2-4	0.062	0.059	1.046
	IG12-1	0.482	0.060	7.977
	IG12-2	0.465	0.071	6.527
	IG12-3	0.349	0.061	5.681
	IG12-4	0.344	0.154	2.232
	E2-1	-0.058	0.029	-1.974
	E2-2	0.072	0.040	1.801
	E2-3	-0.086	0.043	-2.020
Break dates	E2-4	0.016	0.040	0.400
79	Constant-1	-0.014	0.002	-5.919
119	Constant-2	-0.001	0.001	-0.778
183	Constant-3	0.001	0.002	0.305
	Constant-4	0.010	0.002	4.691

Horizon/Group	Regressor	Coefficient	SE	t-stat
6 mo./Group 4	A1G4-1	-0.543	0.040	-13.541
N=209	A1G4-2	-0.623	0.029	-21.492
No. Var = 10	R2-1	0.050	0.038	1.315
	R2-2	0.006	0.029	0.208
	IG41-1	0.470	0.043	10.806
	IG41-2	0.357	0.031	11.503
	E2-1	0.012	0.029	0.412
Break dates	E2-2	0.025	0.022	1.154
70	Constant-1	-0.014	0.002	-6.115
	Constant-2	0.000	0.001	0.262

Note: number after dash in regressor name represents subset of data determined by structural breaks. The number of subsets of data is one more than the number of structural breaks.

Table 3.3 Output for Congruent Models Continued

III: General-to-Specific Models

Horizon/Group	Regressor	Coefficient	SE	t-stat
1 mo./Group 2	Y1G2_1	0.941	0.064	14.600
N=203	Y1G2_2	0.245	0.048	5.130
	Y1G2_3	0.123	0.040	3.070
	A1G2_1	0.416	0.063	6.570
	E1	-0.839	0.036	-23.100
	E1_3	0.157	0.045	3.450
	IG2M	0.851	0.031	27.500
	IG2M_1	-0.406	0.061	-6.610
	IG2M_3	-0.144	0.041	-3.500

Horizon/Group	Regressor	Coefficient	SE	t-stat
1mo./Group 3	A1G3	-0.847	0.025	-34.000
N = 203	E1_1	0.415	0.035	11.900
	E1_2	0.232	0.031	7.450
	IG3M	0.841	0.027	31.500
	IG3M_1	-0.347	0.034	-10.300
	IG3M_2	-0.197	0.031	-6.420

Horizon/Group	Regressor	Coefficient	SE	t-stat
3 mo./Group 1	Y3G1_1	0.476	0.091	5.250
N = 201	A1G1	-0.478	0.083	-5.780
	A1G1_1	0.125	0.041	3.040
	R1G1	0.104	0.017	5.980
	E1	-0.335	0.082	-4.090
	E1_1	0.217	0.030	7.180
	IG1M	0.849	0.030	28.500
	IG21_1	-0.433	0.049	-8.920

Note: number after underscore in regressor name corresponds to number of lags.

Table 3.4 Output for Congruent Models Continued

III: General-to-Specific Models (continued)

Horizon/Group	Regressor	Coefficient	SE	t-stat
3 mo./Group 3	A1G3	-0.774	0.030	-25.900
N = 201	R1G3	0.107	0.024	4.500
	R2	-0.058	0.008	-7.150
	E1_1	0.399	0.037	10.700
	IG3M	0.735	0.033	22.500
	IG3M_1	-0.464	0.041	-11.300
	IG3M_10	-0.065	0.019	-3.380

Horizon/Group	Regressor	Coefficient	SE	t-stat
3 mo./Group 4	Y3G4_1	0.432	0.121	3.590
N=201	Y3G4_2	0.276	0.066	4.150
	Y3G4_3	0.094	0.046	2.060
	A1G4	-0.489	0.099	-4.940
	A1G4_1	0.279	0.069	4.050
	A1G4_2	0.147	0.062	2.380
	R1G4	0.086	0.020	4.370
	R2_1	-0.124	0.033	-3.800
	R2_2	0.105	0.048	2.200
	R2_3	0.008	0.032	0.268
	E1	-0.271	0.102	-2.660
	E1_3	0.044	0.016	2.730
	IG4M	0.783	0.036	21.900
	IG4M_1	-0.425	0.067	-6.340
	IG4M_2	-0.060	0.061	-1.980

Note: number after underscore in regressor name corresponds to number of lags.

References

Abou, A., Prat, G., 2000. Modelling stock price expectations: lessons from microdata. In: Gardes, F., Prat, G. (Eds.), Price Expectations inGoods and Financial Markets. Edward Elgar (Cheltenham, UK), Ch. 12, pp. 271–294.

Bai, J., Perron, P., January 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66 (1), 47–78.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18, 1–22.

Batchelor, R., Dua, P., 1990a. Forecaster ideology, forecasting technique, and the accuracy of economic forecasts. International Journal of Forecasting 6, 3–10.

Batchelor, R., Dua, P., 1990b. Product differentiation in the economic forecasting industry. International Journal of Forecasting 6, 311–316.

Benassy-Quere, A., Larribeau, S., MacDonald, R., 2003. Models of exchange rate expectations: How much heterogeneity? Journal of International Financial Markets, Institutions and Money.

Bryant, R. C., January 1995. The ”exchange risk premium,” uncovered interest parity, and the treatment of exchange rates in multicountry macroeconomic models. Tech. rep., The Brookings Institution.

Cavaglia, S., Verschoor, W. F. C., Wolff, C. C. P., 1993a. Asian exchange rate expectations. Journal of the Japanese and International Economies 7, 57–77.

Cavaglia, S., Verschoor, W. F. C., Wolff, C. C. P., 1993b. Further evidence on exchange rate expectations. Journal of International Money and Finance 12, 78–98.

Cohen, R. H., Bonham, C. S., Abe, S., June 2006. The rationality and heterogeneity of survey forecasts of the yen-dollar exchange rate: A reexamination. Working Paper 06-11, Department of Economics, University of Hawaii Manoa.
URL `http://www.economics.hawaii.edu/research/workingpapers/WP_06-11.pdf`

Doornik, J. A., Hendry, D. F., 1994. PcGive 8.0: An Interactive Econometric Modelling System. International Thomson (London).

Ehrbeck, T., Waldmann, R., February 1996. Why are professional forecasters biased? agency versus behavioral explanations. The Quarterly Journal of Economics 111 (1), 21–40.

Elliott, G., Ito, T., 1999. Heterogeneous expectations and tests of efficiency in the yen/dollar forward exchange rate market. Journal of Monetary Economics 43, 435–456.

Faust, J., Whiteman, C. H., 1997. General-tospecific procedures for fitting a data-admissible, theory-inspired, congruent, parsimonious, encompassing, weakly-exogenous, identified, structural model to the dgp: A translation and critique. Carnegie-Rochester Conference Series on Public Policy 47, 121–161.

Flieth, B., Foster, J., 2002. Interactive expectations. Journal of Evolutionary Economics 12 (4), 375–396.

Frankel, J. A., Froot, K. A., December 1986. Understanding the us dollar in the eighties: The expectations of chartists and fundamentalists. Economic Record, 24–38.

Frankel, J. A., Froot, K. A., March 1987. Using survey data to test standard propositions regarding exchange rate expectations. American Economic Review 77 (1), 133–153.

Frankel, J. A., Froot, K. A., May 1990. Chartists, fundamentalists, and trading in the foreign exchange market. American Economic Review 80 (2), 181–185.

Goldberg, M. D., Frydman, R., July 1996. Imperfect knowledge and behaviour in the foreign exchange market. Economic Journal 106 (437), 869–893.

Griliches, Z., Mairesse, J., 1990. Heterogeneity in panel data: Are there stable production functions? In: Champsaur, P. E. A. (Ed.), Essays in Honor of Edmond Malinvaud. Vol. 3: Empirical Economics. MIT Press (Cambridge, MA and London, England), Ch. 33, pp. 192–231.

Gygax, A., Sawyer, K. R., May 2003. Learning and predictability across events. Tech. rep., University of Melbourne.

Hansen, L. P., Hodrick, R. J., 1980. Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. Journal of Political Economy 88 (5), 829–853.

Hendry, D. F., Krolzig, H.-M., 2001. Automatic Econometric Model Selection using PcGets. London: Timberlake Consultants Press.
URL www.pcgive.com/pcgets/

Ito, T., June 1990. Foreign exchange rate expectations: Micro survey data. American Economic Review 80 (3), 434–449.

Ito, T., 1994. Short-run and long-run expectations of the yen/dollar exchange rate. Journal of the Japanese and International Economies 8, 119–143.

Laster, D., Bennett, P., Geoum, I. S., February 1999. Rational bias in macroeconomic forecasts. Quarterly Journal of Economics, 293–318.

Maddala, G. S., 1992. Introduction to Econometrics, 2nd Edition. Prentice Hall.

Pilbeam, K., 1995. Exchange rate models and exchange rate expectations: an empirical investigation. Applied Economics 27, 1009–1015.

Prat, G., Uctum, R., 2000. The evidence of a mixed expectation generating process in the foreign exchange market. In: Gardes, F., Prat, G. (Eds.), Price Expectations in Goods and Financial Markets. Edward Elgar (Cheltenham, UK), Ch. 11, pp. 251–270.

Trivedi, P. K., 1984. Uncertain prior information and distributed lag analysis. In: Henddry, D. F., Wallis, K. F. (Eds.), Econometrics and Quantitative Economics. Basil Blackwell (Oxford), pp. 173–210.

Appendix 1: Data Description and Variable Definitions

Every two weeks, the JCIF in Tokyo conducts telephone surveys of yen/dollar exchange rate expectations from 44 firms. The forecasts are for the future spot rate at horizons of one month, three months, and six months. Our data cover the period May 1985 to March 1996. This data set has very few missing observations, making it close to a true panel. For reporting purposes, the JCIF currently groups individual firms into four industry categories: 1) banks and brokers, 2) insurance and trading companies, 3) exporters, and 4) life insurance companies and importers. On the day after the survey, the JCIF announces overall and industry average forecasts. (For further details concerning the JCIF database, see the descriptions in Ito (1990, 1994), Bryant (1995), and Elliott and Ito (1999).)

Below we define each of the variables used in the models in the text. Unless otherwise indicated, all variables are in natural logs.

Dependent variables

$YkGi = s^e_{i,t,h} - s_t$ for group $i = 1$, 2, 3, 4, m for mean and horizon $k = 1$ month, 3 month and 6 month.

Adaptive Expectations Regressors

$A1Gi = s_t - s^e_{i,t-1,h}$

A2Gi $= s_t - s^e_{i,t-h,h}$

Extrapolative Expectations Regressors

E1 $= s_t - s_{t-1}$

E2 $= s_t - s_{t-h}$

Regressive Expectations Regressors

R1Gi $= s_{i,t,12} - s_t$

R2 $= \bar{s}_t - s_t$ where $\bar{s}_t = \frac{1}{12}\sum_{l=0}^{11} s_{t-l}$

Interactive Expectations Regressors

IGij $= s^e_{i,t,h} - s^e_{j,t-1,h}$ for $i = 1, 2, 3, 4$, and $i \neq j = 1, 2, 3, 4, m$.